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An Improved Geo-Textural Based Feature Extraction Vector For Offline Signature Verification

Kennedy Gyimah[1] and Justice Kwame Appati[*2] and Kwaku Darkwah[1] and Kwabena Ansah[2]

[1] *Department of Mathematics, Kwame Nkrumah University of Science and Technology, Kumasi-Ghana,*
[2] *Department of Computer Science, University of Ghana, Accra-Ghana*

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Abstract

In the field of pattern recognition, automatic handwritten signature verification is of essence. The uniqueness of each person's signature makes it a preferred choice of human biometrics. However, the unavoidable side-effect is that they can be misused for the purpose of feigning data authenticity. In this paper we present an improved feature extraction vector for offline signature verification system by combining features of grey level occurrence matrix (GLCM) and properties of image regions. Evaluating the performance of the proposed scheme, the resultant feature vector is tested on a support vector machine (SVM) with varying kernel functions and to keep the parameters of the kernel functions optimised, the sequential minimal optimization (SMO) and the least square method was used. Results of the study explained that the radial basis function (RBF) coupled with SMO best support the improved featured vector proposed.

Keywords: Signature Verification; Feature Extraction; Offline Signature Verification; Sequential Minimal Optimization; Kernel Function; Support Vector Machine

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1 Introduction

In the field of pattern recognition, automatic handwritten signature recognition has received a considerable attention to be used for human biometric Diaz-Cabrera et al. (2014c); Hafemann et al. (2017); Impedovo et al. (2012). Enormous studies in the domain of computer science has being carried out in respect of the identification and verification of persons. In this study area, characteristics of biometric that are quantifiable can be measured both physiological and behavioural. An instance to this is the

**Corresponding author: E-mail: jkappati@ug.edu.gh*

fingerprint, DNA and iris of the eye are classified as physiological while signature, handwriting, gait and voice are categorized as behavioural and all these constitute biometrics Neamah et al. (2014). It is well known that every person's signature is unique in terms of its behavioural property and this fact has yield a great community acceptance of its use as biometric for identification and authenticationJain et al. (2004); Fotak et al. (2011). In the light of its popularity, several negative cases of the ease to forge them are recorded motivating the need for an enhanced system for recognition. This systems can either be dynamic or static depending on the structure of the input data Khan and Dhole (2014). In this case, the process of recognition is defined as finding or identifying the owner of the signature whereas the process of verification is to determine whether a signature as forged or genuine. The forged signature comes in various form and are tagged as one of the following that is skilled forgeries Argones Rua et al. (2012) or deliberate forgeries Ferrer et al. (2017) or disguise Liwicki et al. (2012) or random or impostor signatures Gomez-Barrero et al. (2011) or simulated or highly skilled forgeries Ortega-Garcia et al. (2003). A forgery is classified as skilled if the signature is signed by an individual who has done several practices given the genuine one. In simple forgery, the signer has very little knowledge to the genuine signature whereas in random forgery, the signer has no knowledge regarding the signature or the name of the signature owner Shah and Shah (2015).

In the analysis and verification of static signatures, Zois et al. (2016a) presented a grid based template matching scheme. In their study the fine geometric structure of the signature is efficiently encoded with the grid template and partitioned into subsets. Using a five-by-five pixel window binary mask shape for lattice shaped probing structures, features are extracted to detect the ordered transitions. Evaluating the performance of the verification approach on four different datasets of signatures using the Spearman ranking test reveal a strong correlation between complexities. This study continue to prove that the chances of a signature being correctly classified improves significantly when there is an exhibition of a higher quality of genuine samples by signature owners. Following the work of Neamah et al. (2014), the point of gravity centre and the orientation of the skeleton were combined to extract accurate feature patterns for static signature recognition which resulted in a success. Using the writer-independent parameters, Guerbai et al. (2015a) proposed the use of one-class support vector (OC-SVM). In their approach only original signatures are taken into account while the forgery are observed as counterexamples for designing the HSVS system. This approach is very effective for accurate classification on a very large sample however there is inaccuracy in the training of the OC-SVM model which affects performance on insufficient dataset. It is recommended that there is the need for the modification of the decision function used in the OC-SVM which is achieved by carefully adjusting the optima threshold through the combination of various distance metrics used in the OC-SVM kernel. In Paudel et al. (2016), a new online HSV system was proposed to function on low-end mobile devices and reported on the outcome of the experimental evaluation of the system on various dynamic handwritten signature dataset. Finally with the work of Padmajadevi and Aprameya (2016), a review of research works and methodologies were presented in the domain of handwritten signature verification. It is at this point clear that the many works proposed in literature by various authors has a fundamental issue with optimal feature extraction for offline and online signature verification. In this work an improved feature extraction vector is proposed using a blend of glcm and region properties to increase verification accuracy.

2 Preliminary Concepts and Methods

2.1 Image Preprocessing

In signing a signature, persons exhibit varying variations in terms on pressure, posture and even the kind of object used Barkoula et al. (2013); Houmani et al. (2009); Pal et al. (2013b); Wang et al. (2010). There is therefore the need for image normalisation which required the concept of image preprocessing in this context as the first phase of the recognition process. The main aim of the preprocessing is to standardize the signature image and make it ready for feature extraction as well as improving the quality of the image. The series of operations performed chronologically on the signature image is as outlined as follows: binarizationPratikakis et al. (2014); Vo et al. (2018); Karthikaa and James (2015), background eliminationArvind et al. (2007); Diaz et al. (2017), edge detectionZhu et al. (2015) and skeletonizationAbu-Ain et al. (2013); Zois et al. (2016b). Detailing the operations, the grayscale signature image in its raw state is converted into black and white during the binarization process in order to make feature extraction much easier. The background of each binarized image is eliminated. The edge detection operation is then used to compute the boundaries of objects within images by detecting discontinuities in the images brightness. Finally, the skeletonization process is performed to obtain the skeleton of the 2-D binary image of which the required feature can be extracted with ease.

2.2 Feature Extraction

One of the most essential part in signature recognition system is the ability for select accurate sets of features. In this section, two groups of features are estimated namely GLCM properties and region properties Appati et al. (2014b); Hiryanto et al. (2017); Hanusiak et al. (2015); Haralick et al. (1973); Ohanian and Dubes (1992); Ojala et al. (2002); Tamura et al. (1978).

2.2.1 Gray-Level Co-occurrence Matrix (GLCM)

The statistical method used to examine texture and pixels spatial relationships is the gray-level co-occurrence matrix (GLCM). In this matrix, statistical features such as contrast, energy, correlation and homogeneity are computed. These features are defined as follows given the following notations:
$p_{ij} = (i,j)^{th}$ entry in GLCM
$N_g =$ Number of distinct gray levels in the image

1. Contrast
   This is the difference between the highest and the lowest values of the adjacent set of pixels. It is also known as variance or inertia and it is estimated as:
   $$\text{Contrast (con)} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} |i-j|^2 p_{ij} \tag{2.1}$$
2. Correlation
   This is the measure of the linear dependency and it ranges from -1 to 1. This value is zero (0) for a constant image and its computational formulation is given by:
   $$\text{Correlation (cor)} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} \frac{(i-\mu_i)(j-\mu_j)p_{ij}}{\sigma_i\sigma_j} \tag{2.2}$$
   where μ_i and σ_i is the mean and standard deviation of p_{ij} rows , and
   μ_j and σ_j are the means and standard deviations of p_{ij} columns respectively.
3. Energy
   Energy also referred to as Uniformity or Angular second moment measures the uniformity of the texture. This is given by:
   $$\text{Energy (ene)} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} {p_{ij}}^2 \tag{2.3}$$

4. Homogeneity
   This measures the closeness of the distribution of elements in the GLCM to the diagonal of the GLCM. It is also referred to as the Inverse Difference Moment and it is measured mathematically as:
$$\text{Homogeneity (hom)} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g}\frac{p_{ij}}{1+|i-j|} \tag{2.4}$$

2.2.2 Region Properties

Apart from statistically properties of an image, images also exhibit other properties based on their region. A number of such properties exist however in this study only twelve of them are extracted based on their relevance and significant contribution to the proposed feature vector.

1. Area
   The area measures the extent of any two-dimensional figure in a plane. It is given by the integral function:
$$f(x) = \int_a^b f(x)\,\mathrm{d}x \tag{2.5}$$
   where a and b are the two values on the horizontal axis such that $b \geq a$. In image analysis, this is a scalar value representing the total number of pixels in the region of interest.
2. Bounding Box
   This represent the smallest rectangle containing the region. Given an object representation with the set of points
$$\begin{aligned} Q_0 &= (x_0, y_0, z_0) \\ Q_1 &= (x_1, y_1, z_1) \\ &\vdots \\ Q_n &= (x_n, y_n, z_n) \end{aligned} \tag{2.6}$$
   then the bounding box of the object can be established by defining it to be
$$\begin{aligned} \min(x_i) \leq \quad x \quad &\leq \max(x_i) \qquad 0 \leq i \leq n \\ \min(y_i) \leq \quad y \quad &\leq \max(y_i) \qquad 0 \leq i \leq n \\ \min(z_i) \leq \quad z \quad &\leq \max(z_i) \qquad 0 \leq i \leq n \end{aligned} \tag{2.7}$$
3. Centroid
   The centroid or geometric center of a plane figure is the arithmetic mean position of all the points in the shape. This defines the region's center of mass of an image. The centroid of a finite set of k points $x_1, x_2, \ldots, x_k$ in R^n is
$$C = \frac{x_1 + x_2 + \cdots + x_k}{k} \tag{2.8}$$
4. Convex Hull
   Given any set of points in the Euclidean space say X, we define the the convex hull as the smallest convex set that contains X. Mathematically, we have Equation (2.9).
$$\text{Conv(A)} = \left\{ \sum_{i=1}^{|A|} \alpha_i x_i \mid \forall i : \alpha_i \geq 0 \wedge \sum_{i=1}^{|A|} \alpha_i = 1 \right\} \tag{2.9}$$

5. Minor Axis Length, Major Axis Length and Eccentricity
The Minor Axis Length : is the length (in pixels) of the minor axis of the ellipse that has the same normalized second central moments as the region while the Major Axis Length is the scalar value specifying the length (in pixels) of the major axis of the ellipse that has the same normalized second central moments as the region. The eccentricity on the other hand determines the ratio of the distance between the foci of the ellipse and its major axis length. This property has a range of 0 to 1 where 0 and 1 are degenerate cases; thus an ellipse with eccentricity of 0 is a circle, while an ellipse with eccentricity of 1 is a line segment. Given Equation (2.10) as an ellipse
$$\frac{(x-h)^2}{a^2} + \frac{(y-k)^2}{b^2} = 1. \tag{2.10}$$
where (h,k) is the center of the ellipse and (x,y) being any arbitrary point in the x-y plane, we represent the major axis as:
$$a = r_{min} + r_{max} \tag{2.11}$$
and the minor axis as
$$b = 2\sqrt{r_{min} r_{max}} \tag{2.12}$$
where r_{max} and r_{min} are the maximum and minimum distances from the focus to the endpoints of the ellipse. Given the definition, the eccentricity of the ellipse is formulated as
$$e = \sqrt{1 - \frac{b^2}{a^2}} \tag{2.13}$$
6. EquivDiameter
This parameter specifies the diameter of a circle with the same area as the region and is computed as:
$$\sqrt{\frac{4 * Area}{\pi}} \tag{2.14}$$
7. Euler Number
This specifies the number of objects in the image minus the number of holes in those objects. The Euler Number is given by
$$E = N - H \tag{2.15}$$
where N is the number of regions of the image (number of connected components of the object) and H is the number of holes in the image (isolated regions of the background of the image).

With these region properties including Extent, Extrema, Orientation, Solidity, ConvexArea and Perimeter, the mean and variance is computed giving a sum of twenty-eight features of the region properties. Adding these to the GLCM features gives a total of thirty-two features extracted from each signature image. These extracted features are then pass to a classifier. In this study the support vector machine is used as detailed below.

2.3 Support Vector Machine (SVM) Classifier

One major tool that is used purposely for both classification and predictive regression is the support vector machine (SVM)Cortes and Vapnik (1995); Chang and Lin (2011); Diaz-Cabrera et al. (2014b,a); Gruber et al. (2010). In order to maximize the accuracy of any prediction with low computational complexity, this machine learning based theory is used. Having different objects with different class of memberships, the SVM seeks to draw a decision plane between these set of objects and classify them. For any two given classes, the SVM classifies the data points by providing the best hyperplane that separates one class from the other. In practice, the hyperplane with the greatest margin between the two classes is considered the best hyperplane. The nearest data points to the separating hyperplane which is assumed to be linear represent the support vectors. Unfortunately, not all data are linearly separable hence the need to modify the decision function using kernel tricks.

2.3.1 Kernel Functions

For a non-linear separable set of training data, kernel functions are used by implicitly mapping the non-linear separable input space into a linear separable feature space, where the linear classifiers can be appliedAppati et al. (2014a); Zhang and Li (2012); Pal et al. (2013a); Guerbai et al. (2015b); Ferrer et al. (2013). The kernels transform the input data into the required form by finding the inner product between two points in a suitable feature space. Some common kernels used with SVM are

1. Polynomial kernel:
   Training samples that are similar in the feature space are represented by the polynomial kernel over polynomials of the input space (original variables) and this allows learning of non-linear datasets. It is formulated as :
   $$K(X_i, X_j) = (X_i \cdot X_j + c)^d \tag{2.16}$$
   where X_i and X_j are vectors of the training samples, d is the degree of the polynomial and $c \geq 0$ is a free parameter trading off the influence of higher-order versus lower-order terms in the polynomial.
2. Gaussian radial basis function (RBF):
   Given any two samples X_i and X_j, the Gaussian radial basis function (RBF), representing the feature vectors in some input space, is defined as
   $$K(X_i, X_j) = exp(-\gamma \|X_i - X_j\|^2) \tag{2.17}$$
   where $\|X_i - X_j\|^2$ is the squared Euclidean distance between the two feature vectors X_i and X_j and $\gamma > 0$.
3. Multilayer Perceptron (MLP) kernel:
   The Multilayer Perceptron (MLP) kernel which is also known as the Hyperbolic Tangent Kernel or the Sigmoid Kernel is formulated as
   $$K(X_i, X_j) = tanh(\alpha X_i \cdot X_j + c) \tag{2.18}$$
   for some $\alpha > 0$ and $c < 0$

2.4 Parameter Estimation

From the kernel function defined, there is the need to estimate the various parameters that explains the kernel function more appropriately given the dataset. In this study, two methods are considered that is: Sequential Minimal OptimizationOsuna et al. (1997) and the Least Square Suykens and Vandewalle (1999) as explained in detail the following subsection.

2.4.1 Sequential Minimal Optimization (SMO)

In this procedure, the SMO seeks to divide the optimization problem into a series of smaller possible sub-problems and solved analytically. By illustration, consider a given dataset $(x_1, y_1), (x_2, y_2), (x_3, y_3), \ldots, (x_n, y_n)$ where the input vector is x_i and $y_i \in \{-1, +1\}$ a binary label that corresponds to each x. The SVM is trained to solve this Quadratic Programming (QP) problem expressed below;

$$\text{max} W(\alpha) = \sum_{i=1}^{m} \alpha_i - \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{m} y^{(i)} y^{(j)} K(x_i, x_j) \alpha_i \alpha_j, \tag{2.19}$$

subject to the constraints:

$$0 \leq \alpha_i \leq C, \quad \text{for} \quad i = 1, 2, 3, \ldots, m, \tag{2.20}$$

$$\sum_{i=1}^{m} y^{(i)} \alpha_i = 0 \tag{2.21}$$

where $K(x_i, x_j)$ is a kernel function, C, a hyperparameter and α been the Lagrange multipliers. Since the constraints are linearly equal and involves the Lagrange multipliers α, the least possible problem has two of such multipliers. The constraints for the two multipliers α_1 and α_2 is therefore reduced to:

$$0 \leq \alpha_1, \alpha_2 \leq C, \tag{2.22}$$

$$y^{(1)} \alpha_1 + y^{(2)} \alpha_2 = k \tag{2.23}$$

which is solved analytically and k is the negative of the sum over the rest of the terms in the equality constraint, and this has a fixed value for each iteration.

2.4.2 Least Squares Optimisation (LS)

Consider a given dataset $(x_1, y_1), (x_2, y_2), (x_3, y_3), \ldots, (x_n, y_n)$ where the input vector is x_i and $y_i \in \{-1, +1\}$ a binary label that corresponds to each x. The SVM satisfies the following conditions as:

$$\begin{array}{rcl} w^T \varphi(x_i) + b & \geq & 1, \quad \text{for} \quad y_i = 1 \\ w^T \varphi(x_i) + b & \leq & -1, \quad \text{for} \quad y_i = -1 \end{array} \tag{2.24}$$

Rewriting Equation (2.24) into a single equation we have the following:

$$y_i(w^T \varphi(x_i) + b) \geq 1, \quad i = 1, 2, \ldots n \tag{2.25}$$

where $\varphi(x_i)$ is the nonlinear function that maps the original input space into a higher dimensional feature space. In instances where the hyperplane that separates the two data does not exists, a slack variable ξ_i is introduced such that the optimization problem becomes:

$$\text{minQ}(w, \xi_i) = \frac{1}{2} w^T w + c \sum_{i=1}^{n} \xi_i \tag{2.26}$$

subject to:

$$\begin{array}{r} y_i(w^T \varphi(x_i) + b) \geq 1 - \xi_i, \quad i = 1, 2, \ldots n \\ \xi_i \geq 0, \quad i = 1, 2, \ldots, n \end{array} \tag{2.27}$$

For the Least squares SVM classifiers, the minimization problem is reformulated as:

$$\text{minQ}(w, b, e) = \frac{\mu}{2} w^T w + \frac{\gamma}{2} \sum_{i=1}^{n} e_i^2 \tag{2.28}$$

which is subject to the inequality constraints

$$y_i(w^T \varphi(x_i) + b) \geq 1 - e_i, \quad i = 1, 2, \ldots n \tag{2.29}$$

with $e_i = (y_i - (w^T \varphi(x_i) + b))$ where both μ and γ are considered as hyper-parameters which tunes the amount of regularization versus the sum of squared error.

2.5 Performance Evaluation of Proposed Features

The parameters used in measuring the performance of the system are the False Acceptance Rate (FAR) and False Rejection Rate (FRR)Amoako-Yirenkyi et al. (2015). The False Acceptance Rate (FAR) measures the probability that the biometric security system will falsely accept an unauthorized person accessing the system. This is usually referred to as the Type - II error. The lower its value the better and vise-versa. The False Rejection Rate (FRR) on the other hand measures the probability that the biometric security system will falsely reject an authorized person accessing the system. Again, this is also referred to as Type - I error. Similarly, the lower the FRR the better and vise-versa.

3 Proposed Framework

This section presents the proposed framework for the verification of offline signature. As shown in Fig. 1, the GPDS image dataset is partitioned into two sets (training and test) with each set pre-processed while geometric and textual are being extracted to for the train and test feature vector respectively. The train feature vector are then trained to generate models which are evaluated using the test feature vector with the best performing model that well explain the dataset selected.

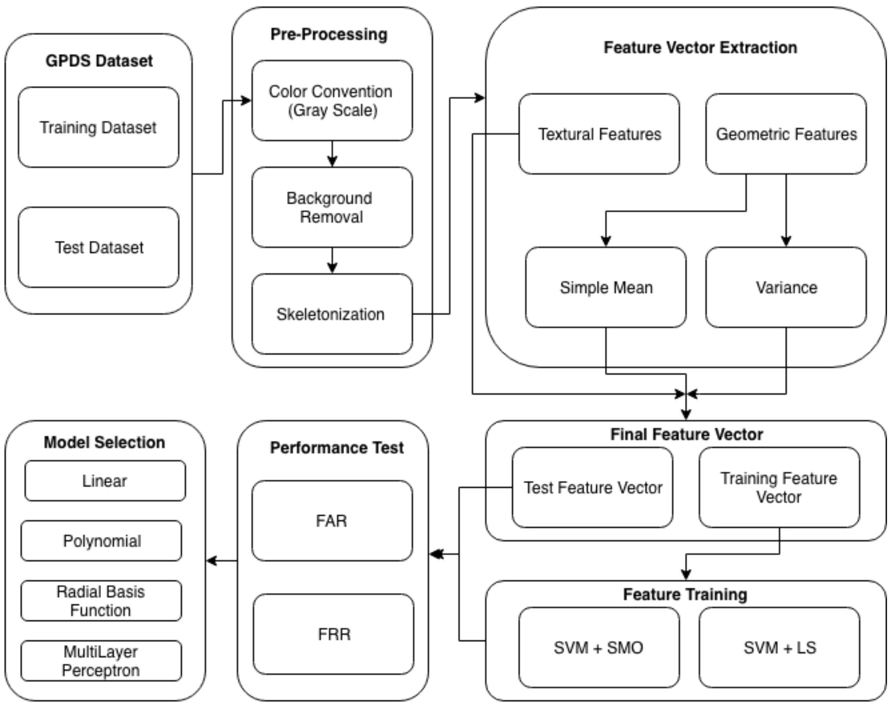
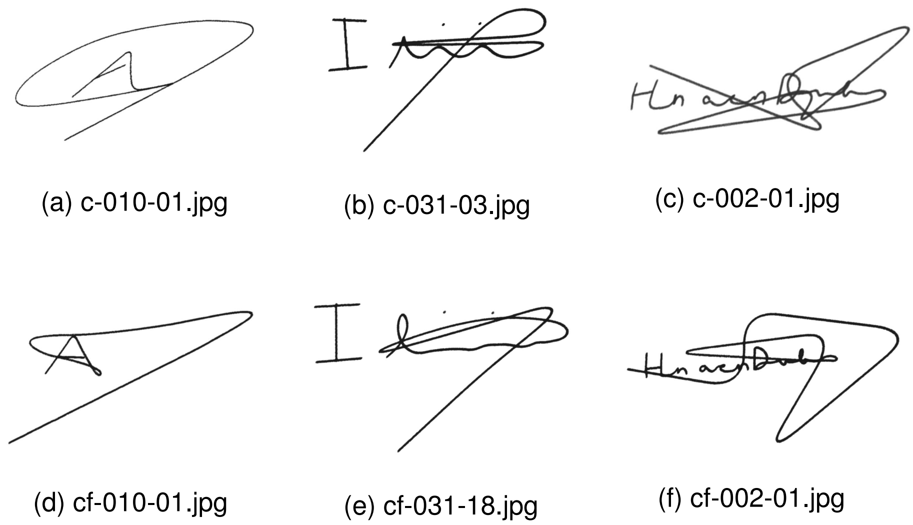


Figure 1: Proposed Framework

4 Results

4.1 Dataset Selection

This study used the Grupo de Procesado Digital de Senales (GPDS) dataset to evaluate the proposed framework Ferrer et al. (2013). This is to help make a valid conclusion since most published research in this field make use of this dataset and hence serving as a standard for analysis. The dataset consists of signatures from 4000 individuals, each having 24 genuine signatures and 30 forged signatures. Fig. 2 shows three genuine and three forged signatures from three distinct individuals.



(a) c-010-01.jpg (b) c-031-03.jpg (c) c-002-01.jpg

(d) cf-010-01.jpg (e) cf-031-18.jpg (f) cf-002-01.jpg

Figure 2: Three sample images each of genuine and forged signatures

4.2 System Requirement

The proposed method was implemented on a system with the following features as a proof of concept:

1. machine brand: Lenovo thinkpad x270
2. memory: 16GB
3. processor: intel i7, 2.4GHz
4. operating system: Ubuntu 16.04LTS
5. application: MATLAB 2016a

4.3 Experimental Result

In this article the support vector machine (SVM) was used to train the extracted feature vectors. Since SVM is parametric by definition, it is important that these parameters are fine tune optimally to explain the given dataset. The key parameters here are the choice of the Kernel function and the optimisation scheme for the parameter fitting. In the case of the Kernel function, options such as linear, quadratic, polynomial, radial basis function and multilayer perceptron was considered. Each of these options also comes with some set of parameters which require fine tuning. After varying these local parameters and observing their influence on the overall performance Table 1 and Table 2 was obtain. Table 1 was obtained with the use of Sequential Minimal Optimisation method while Table 2 was obtain using the Least Square methods.

Table 1: FAR and FRR Values using SMO Method

Kernel Function	FAR	FRR
Linear	18.33	43.96
Quadratic	17.78	0.07
Polynomial	14.78	0
RBF	2.50	0.14
MLP	2.67	97.71

Table 2: FAR and FRR Values using Least Square Method

Kernel Function	FAR	FRR
Linear	5.82	89.92
Quadratic	11.44	45.44
Polynomial	7.49	0.69
RBF	2.29	0.75
MLP	0.71	97.78

For a better appreciation of the feature engineering method proposed, we compare our method to other four current existing methods using the same dataset and performance measure. Results from the comparison is shown in Table 3.

Table 3: Experimental results obtained for GPDS dataset. A comparative analysis

Proposed by	Feature	FAR	FRR
Vargas et al. (2011)	GLCM	6.17	22.49
Guerbai et al. (2015a)	Curvelet Transform	19.4	12.5
Shekar et al. (2015)	Pattern Spectra	8.94	8.59
Hafemann et al. (2016)	Feature Learning	3.53	3.94
proposed approach	GLCM + Region Properties	2.50	0.14

4.4 Discussion

Theoretically, it is expected that the performance metric (FAR and FRR) will be zero indicating error intolerance of signature verification. However, in practice this is usually not feasible due to a number of factors. From the experimental results shown, one may think the polynomial function of the SMO method will make a good model since it has a zero value for FRR. Unfortunately this is not the case as it has a higher value of FAR. This implies the need of a trade-off between FRR and FAR. Using this concept, one may now settle on RBF model for both methods (SMO and LS) but the question of which method to hold-on to becomes necessary. Here, the error margin between the two method is evaluated. This gives a value of 0.21 (2.50 - 2.29) for FAR comparison and 0.61 (0.75 - 0.14) for FRR comparison. Clearly 0.61 is relatively higher than 0.21, hence the best model that well explain the given dataset using our proposed method is the RFB with SMO optimiser.

5 Conclusion

In conclusion, an improved geo-textural based feature extraction vector is proposed and trained with Support Vector Machine. Methods such as Sequential Minimal Optimisation and Least Square was used with five learning models (Linear, Quadratic, Polynomial, Radial Basis Function and Multilayer Perceptron). The results show that SVM with the RBF model and SMO method performs well on the data sample with FAR value of 2.50 and FRR value of 0.14. Besides the proposed method also out perform the existing methods quite significantly make it a choice to be considered in real time implementation.

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